Machine Learning Approaches to Real-Time Quality Control in Automotive Assembly Lines

[1] **Dwaraka Nath Kummari,**
Software Engineer, ORCID ID: 0009-0000-4113-2569

Article Info
Page Number:16801 - 16820
Publication Issue:
Vol 71 No. 4 (2022)

Article History:
Article Received: 15 October 2022
Revised: 24 November 2022
Accepted: 18 December 2022

Abstract

Autonomous Deep Quality Monitoring in Streaming Environments Monitoring plays a vital role in today's manufacturing industries due to its positive contribution toward the increase of productivity, safety of manufacturing operations, and reduction of manpower. It maximizes the lifespan of equipment, avoiding unnecessary downtime and ensuring the quality of the end product. Real-time quality monitoring is highly demanded because the common practice in the industry is deemed too labor-intensive as a result of multi-staged visual inspection. Accurate quality monitoring is important to attain high customer satisfaction and to meet the product's standard. Manual quality checks are limited in capacity, requiring time-intensive efforts, which increases costs for companies significantly. This has led to an in-depth study in utilizing data-driven approaches to fully automate quality monitoring of manufacturing products. Data-driven quality monitoring is developed through two steps, indirect sensing and monitoring, which circumvents high development time as is the case for analytical models. The models are capable of diagnosing possible defects of end products without manual intervention. Various approaches have been presented to deliver a reliable data-driven quality monitoring approach. Who supervises the supervisor? Model monitoring in production using deep feature embeddings with applications to workpiece inspection The automation of condition monitoring and workpiece inspection plays an essential role in maintaining high quality and throughput of the manufacturing process. The recent rise of developments in machine learning has led to vast improvements in autonomous process supervision. One of the main challenges is the monitoring of live deployments of these machine learning systems and raising alerts when encountering events that might impact model performance. Supervised classifiers are typically built under the assumption of stationarity in the underlying data distribution. A visual inspection system trained on material surface defects does not adapt or recognize gradual changes in the data distribution, known as 'data drift'. It is desirable to provide real-time tracking of a classifier’s performance to inform about the onset of additional error classes and the necessity for manual intervention with respect to classifier re-training. Today's increased level of automation in manufacturing requires the automation of material quality inspection with minimal human intervention. Companies strive to achieve both quantity and quality in production without compromising one over the other. With advancements in Artificial Intelligence, companies employ such technologies to automate quality inspection and monitor machine conditions, thereby minimizing human intervention and optimizing factory capacities. One such event may be a gradual or abrupt drift in the data distribution.

Keywords: Automotive assembly lines, quality management, smart industry,Real-Time Monitoring,Defect Detection,Predictive Maintenance,Sensor Data Analytics,Supervised Learning,Anomaly Detection,Computer Vision,Edge Computing,Time Series Analysis,Process Optimization.Platform; Diversity Measurement in Students Data Education Knowledge Platform; Learning Analytics Dashboard; Industry 5.0.

1. Introduction

The growing demand for manufacturing needs leading industry to improve the productivity, quality of the product, maintainability and controllability. One of the most important industries today is the automotive industry. Automotive parts exhibit a high diversity in terms of sizes, shapes and constituent materials. This enormous diversity leads to a high complexity in quality inspections since an appropriate inspection strategy must be determined for each type of auto part. Hence, new parts are demanded to be inspected with several manually determined parameters based on the process characteristics, which is extremely labor and time consuming. To avoid human errors and to improve the stability and reliability of the inspection process, it is preferable to conduct fully automatic quality control in a robust and reliable manner. The fast development of computer vision technologies has provided a wide range of solutions to potentially replace human workers, such as deep learning. With the appearance of various vision sensors, inspection data can be gathered in the form of high dimensional images and videos. Although deep learning approaches have been widely applied in various areas of inspections, they are not robust and credible enough to replace human inspectors. If unseen and extremely faulty parts undergo tests, it will be impossible to detect them.

Hence, the model must adapt dynamically to the variations of the input data under and out of the operating environment. The assembly process is crucial in automotive manufacturing, but adequate robustness and reliability of possible errors in pick-up, in-motion and mounting have not been fully investigated. With the growing demand on lower cost and higher performance of assembly processes, and the stringent requirements for lower consumption and higher quality in automotive products, those maskable picked up assemblies must be carefully inspected in real-time on-site. Since the reliance on human inspection is facing limits of efficiency, accuracy and cost, it is essential to develop a robust and reliable perception approach to automatically inspect the faulty results. A fast and robust perception approach based on deformable part models (DPM) is proposed for the vision based quality monitoring in automotive assembly. It can detect the mounted assemblies precisely and efficiently in the factory before problems arise.

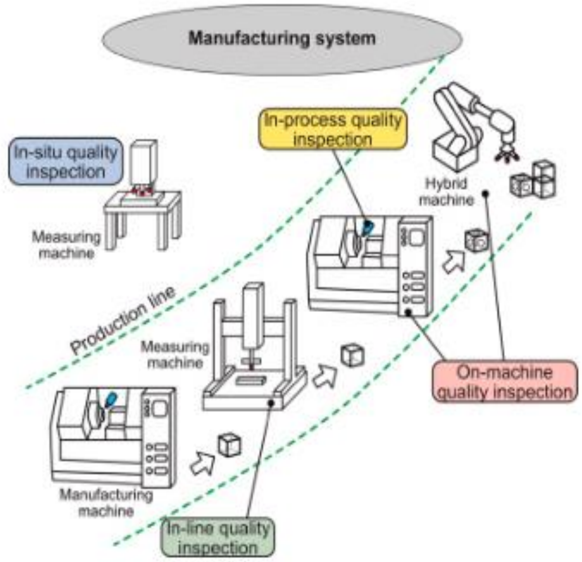

Fig 1: Automation for in-line quality inspection

1.1. Research design This research encompasses various areas of Knowledge Discovery and Data Mining (KDD). The goal is to help production engineers with proactive Quality Control (QC). The focus is on using and developing mathematical models in the context of predictive modeling for classification. The first objective is to present a methodological approach for building a classifier ensemble to apply Proactive Quality Control (PQC) in a non-trivial real-world problem. The ensemble relies on four different types of classifiers: decision tree, kNNs, multilayer perceptron, and SVM classifiers. In addition, the accuracy of the proposed models is analyzed on a real-world quality monitoring problem, with a particular focus on the impact on the quality of the prototypes and the modeling efforts on the choice of classifier types, selection criterion, and fusion process of classifier ensembles.

To provide a proactive QC, predictive models are developed and implemented in production pipelines. The modeling framework comprises data collection and data mining phases, where the latter includes potential preprocessing, learning, and post-processing tasks. The focus is on the data mining tasks regarding classification problems in manufacturing. Firstly, how to use supervised learning methods to detect defective workpieces in production is proposed. Then, modeling post-processing techniques are discussed regarding using a classifier ensemble for diagnosing and retraining choices on industrial data. The proposed classifier ensemble is a robust and easy-to-maintain model for these tasks. The performance of the classifier ensemble is assessed on the basis of an extensive experimental evaluation considering different learning, selection, and fusion options for a large diversity of real-world scenarios.

Equ 1: Optimization Objective (General ML Loss Function)

$$\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(\hat{y}_i, y_i)$$

Where:

- $\hat{y}_i = f(\mathbf{x}_i; \theta)$
- $\mathcal{L}$ is a loss function (e.g., cross-entropy or MSE)

2.

Background and Motivation

The automotive industry is currently witnessing a significant resurgence and development, mirrored in the growing demand and complexity of cars and vehicle systems. Only eight years ago, a simple communication bus could suffice to connect a dozen controllers, while today there are multiprocessor CPU systems that employ optical connections to handle more than a hundred different nodes in one vehicle. The rapid evolution of both hardware and software necessitates the usage of advanced methodologies during the development cycle, the implementation of which also introduces many engineering challenges. A critical challenge, whose effective resolution is required for the general acceptance of large-scale usage of advanced vehicle development approaches, is the maintenance of a vehicle's assembly process' quality and stability.

The concept of quality, handled successfully by the automotive industry until present, can be formally expressed as, for given process parameters K, the systems denoted as ϕQ have closed-loop control (monitoring) that assures their realization provides output results Y closely following pre-defined, explicitly stated, expected values W. It is a valid assumption that automotive assembly processes have been designed to be as well-behaved as possible, in the sense that the paths φℓ,K(Y) are continuous and differentiable functions of the inputs K, and the processes possess pre-defined, explicitly-stated interactions. However, as the complexity of vehicle assembly lines and their strict symmetry and bias constraints increased in parallel with the evolution in variety and richness of vehicle systems, there came a technological point when the complexity became too great for off-line design.

In the assembly system's quest for structuring, the events denoted by φ are repeatedly and consistently generated at predefined bin-points, using a large number of assembly tools and parameters. This consistency appears as a successful repeat of the pre-defined goal state but at the same time results in the generation of very similar output results Y. Lacking any input perturbation, standard feed-forward/feedback control loops often do not provide information on process changes. In addition, the introduction of assembly line post processing and reflective relations has added the requirement of assessing process integrity and stability.

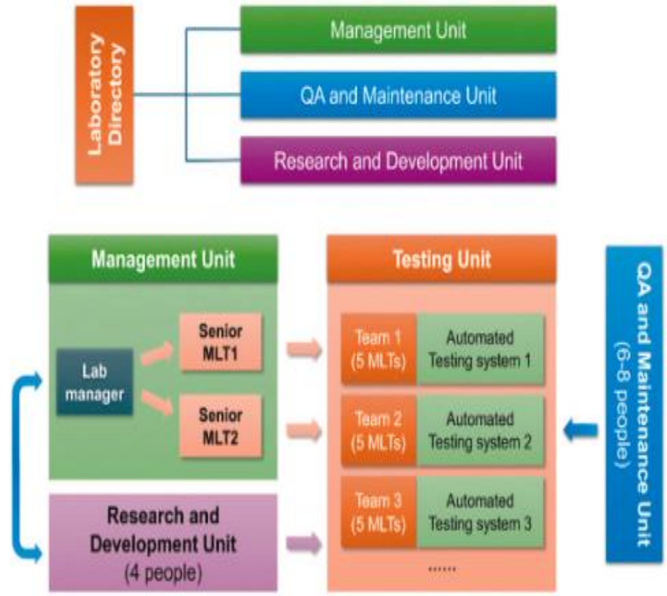

Fig 2: Background and Motivation

3. Overview of Quality Control in Automotive Manufacturing

Quality can be described as the perceived excellence of a product or service. It includes the complete set of characteristics of a product or service that bears on its ability to meet the declared or implied needs of the customer. Quality control (QC) involves activities that are part of the quality management system and are intended to ensure that the necessary quality requirements are met. The importance of ensuring product quality is reflected in the significant growth in the resources devoted to quality assurance and the rapid growth of the quality assurance and metrology industries. The increasing use of machine vision in automation is leading to Intelligent Quality Assurance Systems capable of using AI to determine the outcome of visual inspections.

Automotive assembly line manufacturers supply fully equipped vehicles after an assembly process that takes place in an automotive assembly line. Acceptance of products relies heavily on visual inspection by trained operators, who use human vision and quality inspection plans to assess the quality of finished vehicles and release or reject them through a final quality control (FQC) process at the end of the assembly line. The capacity of a robotic inspection system is currently limited to about 20% of that of a human, and its efficiency is limited as a new robot must be programmed for each new vehicle type when the vehicle design changes. An FQC system capable of using robotic inspection systems is desirable, allowing for maximum utilization of inspection resources. It is also necessary that the system accepts incrementally added QC tasks, which are enabled by the ability to identify inspection resources equitably among continuously detected defective products.

Fig 3: Quality Control in Automotive Industry

3.1. Historical Context Whether it is to catch faulty products at an early stage of production or to ensure that the visual aspects of manufactured products conform with the requirements, automated visual inspection is fundamental to manufacturing. In manufacturing, there are various visual aspects that may be required together with certain concepts of acceptance/rejection. To assure that continuous production is not hampered, taking actions on defects needs to be done as fast as possible. As such, it seems imperative to consider real-time visual inspection options. Automated visual inspection is a computer vision and/or image processing application that focuses on quality control in manufacturing. This is often done by taking images of the products and extracting relevant features for these images. Machine learning models are subsequently trained upon using these features to classify the products. In recent years, with the rapid advancements in deep learning models, the process of automated visual inspection has changed considerably. With the invention of convolutional neural networks, the feature extraction part in machine vision has been simplified/automated. In this paradigm, a deep learning model takes the input images directly and performs both the feature extraction and the classification side. Because of the generality of the performance of trained models, automated visual inspection has been a hot topic in various cases of manufacturing. From a parental car seat to brakes, automated visual inspection with machine learning models has been used to produce images on a feasible time scale. In all such work however, the comparison was done with a group of machine learning models but it could happen that there is better performance with a known state-of-the-art model of another library or another approach (such as transformers). As such, it may be beneficial to have shared repositories of benchmark datasets with a fair comparison and thorough evaluation. Furthermore, deep learning architectures and implementations ballooned in size to the point that recreating them from scratch is an impossibility, calling for shared references and perhaps even a common core or components.

3.2. Current Practices Traditionally, the development of an automotive assembly process begins with a 3D CAD model. Based on the design intent, an assembly process plan is created that provides the sequence of assembly operations along with their parameters. The fixture design takes into consideration the assembly process model, product nominal data, and assembly location. It determines the position and orientation of the parts in the assembly system and essentially forms a closed loop in the design/engineering of the assembly process. For each operation, the designed fixture and associated assembly machines are used to assemble mass-produced parts. Throughout the life cycle of the assembly process, these assembly operations are executed using the assembly equipment and fixtures under the guidance of initial process plans. Major assembly operations generally involve the relative motion of dedicated fixed/automated fixtures, with regard to which parts-location combinations must be within a specified tolerance in order to ensure quality assembly. Fixture-based assembly is robust; yet, if there is unexpected excessive wear-and-tear of the fixture or shift of the part-location relationship due to mis-threading jigs or errors in the handling robots, incorrectly located/dimensioned parts will on occasion show up at the assembly benches.

Preventive maintenance approaches have to some degree been adopted to manage the deterioration of assembly equipment and fixtures. However, few methods exist that can pinpoint assembly faults to their root causes. After corrective actions are taken, a new batch of assemblies still needs to go through extensive and costly off-line quality checks. There is a strong motivation for enabling assembly process engineers to conduct on-line/pervasive fault diagnosis and corrective actions even under strong coupling of fixture and part geometries, responsibilities and thus, expectations during the assembly process. Allowing undisturbed flow of parts with excessive errors to the assembly process is a common yet unfavourable situation. Typically on-line measurement of parts and fixtures is not possible at every instance of the assembly process, and with the services of special-purpose measurement jigs, any qualitative/quantitative diagnosis and corrective actions would only be done at off-line locations. Poorly designed assembly process systems on the other hand are non-robust and tend to be very sensitive to variation.

Equ 2: Reinforcement Learning (Adaptive Quality Control Adjustment)

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

Where:

- s: current machine state
- a: action (e.g., adjust torque)
- r: reward (based on improved quality)

4. Machine Learning Fundamentals

Machine learning methods can focus on supervised and unsupervised learning forms. Supervised learning occurs when a model is trained using predefined input and desired output, while unsupervised learning finds structures from unlabeled data. Unsupervised algorithms work without annotating the objects of interest and improve machine learning methods used for categorical classification. A new kind of hybrid strategy combining semi-supervised and self-supervised learning with fully automated labeling was examined, resulting in the development of a self-supervised framework for workpiece inspection during machining.

Deep learning is a subcategory of machine learning algorithms and can be applied to a wide range of fields, including image classification. Applied machine learning becomes a data-intensive process and depends on both data and experiences. Advantages of creating fully automated, intelligent, and real-time quality control methods for various industrial vision applications are discussed. Artificial intelligence tools must also fulfill industrial and technological requirements such as real-time processing, high robustness, and high accuracy. Video data is significantly different from single frame images. A novel intelligent algorithm working in real time on the GPU is proposed, learning a detection network to rapidly identify handling faults of various industrial polymers.

Reduced robustness and shifting data distribution are confronting challenges of newly introduced learning techniques for defect detection tasks. A small database of defects is trained with few-shot classification networks to detect defects of similar types compared to the training examples, but does not detect new types. The probability distribution function of defects in production is unknown, and defects emerge as products circulate in the production line. Data drift detection monitors distribution changes of numerical variables over time. Statistical and machine learning approaches need to process non-time-series variables to detect similar events occurring as time series over a fixed time interval.

Novelty detection works on both numerical and image data and identifies anomalies outside the training dataset, but requires distribution assumption and normal samples only. Data drift detection is application-independent and can address non-time-series variables, but typically considers only variance, shift, and degree extinction. Data drift detection was used to estimate both raw and feature embedding to identify drift events in the unsupervised domain. To deploy ordinal regression headings in a categorical classifier, ordinal class embedding must be added.

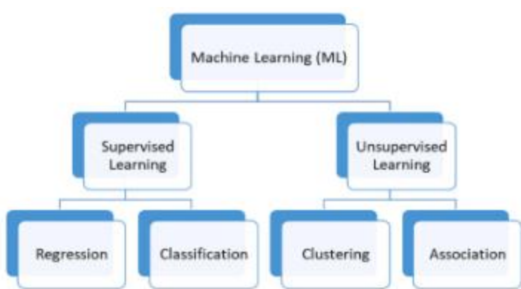

Fig 4: Machine Learning Fundamentals

4.1. Types of Machine Learning In recent years, Machine Learning (ML) has become a buzzword in various industries. Countless applications have emerged, and new academic publications appear almost daily. This section serves as a brief overview of the most common types of ML to provide a better understanding of the methods applied in later parts of this article. The class of ML can generally be divided into supervised, unsupervised, and reinforcement learning. A commonly used subclass of supervised learning is regression. In this case, the model is trained with input data and known numerical values. The trained model can be used to predict the expected numerical output for a new input, which is helpful for various practical applications. The second subclass of supervised learning, classification, aims to distinguish training images belonging to different classes (labels). A deep learning-based supervised classifier is usually built as a multi-layered neural network. An input image is processed layer-wise and converted into a latent feature representation that is typically combined using a fully connected layer, processed by an activation function, and transformed into predicted class probabilities. As mentioned above, supervised learning requires labeled data with the same distribution as the training data. Since the training set does not cover the complete input space, the classification model will not perform well whenever unseen data is detected or the production system undergoes changes. Thus, unsupervised learning aims to provide two things: the exploration of unannotated data to find a more informative representation of the underlying distribution and the classification of true unlabeled data. Unsupervised approaches are typically used for visualizing high-dimensional data in lower dimensions. A generative pre-trained model that transfers the problem to data generation is a widely used unsupervised learning approach. Automatic generative models of deep learning have attracted a lot of attention in recent years and are seen as a promising new avenue in unsupervised learning. In recent publications, great performance in text and image generation has been achieved. In the transfer learning stage of CPT, the parameters of the pre-trained generative model are preserved, and a discriminator is trained to distinguish between real and generated data. An existing classification model is used for feature extraction, and these features are passed on to the classifier.

4.2. Key Algorithms Classification models used for analysis are tailored for their respective tasks. One can select from one or multiple algorithms, pre-defined ones (like SVM, Random Forest, KNN, and NN) or custom ones based on different prior knowledge on the task. The basic setup, e.g. parameters for SVMs, is frequently optimized to obtain the most suitable settings for the specific task. One can also combine multiple algorithms or algorithms with pre/post-processing steps like first segmenting the part of a structure that is then analyzed by the classification model.

Deep networks found widespread application due to their performance and readiness to use. Model architectures are available off-the-shelf or training on an own dataset is possible (transfer learning). Convolutional networks are especially appropriate for real-time image analysis since they can operate on the original image size, which allows for very fast calculation. Overhead stems from specific preparation and image resizing. Concatenation, e.g. combining various cuts of the same image together, can allow for even faster computation. Modification and improvement of the model architecture customize it to specific needs.

Edge cases with surprisingly low classification rate arise. Ones in the reference and evaluation set are gauged on the gradient of the network. They indicate local areas of performance deterioration in the parameter space. Accounting for this finding during design provides guidance to architecture changes to be made. Robustness against fallbacks and useful modifications like prediction horizons are easily possible.

5. Data Acquisition and Preprocessing

The proposed image acquisition module consists of a camera head with a lens and illumination designed together. They were placed on a servo-controlled articulated robotic arm. The camera was selected according to the imaging scheme: it must have a high resolution (5400 x 3600) and even illumination. The lens illumination must cover the entire field of view (33.5 mm x 20.6 mm). The automatic iris control was developed and the operation of the lighting control system was verified before the implementation of the detection system. The camera head uses a lens with controlled illumination, which allows the depth of field to be changed. In this way, it is possible to remove interference or focus on the detail, depending on the type of object. The moving part created a problem for the detection of the object. A working cycle was developed, in which outputs corresponding to the triggering of subsequent processes were isolated. The operation of only one process was analyzed, that is when the camera was triggered. In subsequent versions, other commands will also be taken into account throughout the work cycle of the production line.

CAM objects are variable (both geometrically and in terms of texture), but at the same time they can still be trained for many object classes (many fields for each class). The introduction of a state-of-the-art convolutional neural network (CNN) was proposed, the implementation of which was carried out in Python using TensorFlow. Data were collected that included both good examples (6350 images) and abnormal examples (861 images). Training was performed on low-resolution images (640 x 432) containing both objects (40% of the image) and noise (background). Using class weights in loss functions allowed good object detection at the test stage (98.24%). The detection of CAMs showed the right localization as well as the high quality of the circle detection. In edge cases where CAMs overlap with noise, misdetected positions remain, but they do not disturb further classification of the detected object.

5.1. Sensor Technologies

Different sensor technologies exist to acquire the information required to evaluate the quality of the assembly process. The most widely used ones in automotive assembly applications are covered in this section, starting from one dimensional inline systems and progressing to two dimensional offline systems. Each system implementation is complemented with details on its suitability for the evaluated tasks, the advantages it brings, and the problems that hinder their further use. A preliminary comparison of the reliability and the cost of each approach is also included. Last but not least, advances in sensor technologies that expand the capabilities of traditional sensors and make them more competitive alternatives are elaborated on. In addition to the classical approaches, newer sensor technologies whose feasibility is still to be proven in automotive assembly as of now are also emphasized.

1D inline systems are the baseline quality control for automotive assembly. Their procedure can be broken down into detection of some reference points, trouble finding incorrect position identification, and fitment evaluation. Although the basic concept of the devices is simple, the low-cost sensors, the multiple scanning techniques used, the level of automation involved, and many other characteristics make the quality control with this technology quite complex. With advanced optical scanning systems, however, 1D sensors easily fall short in the detection performance. The devices based solely on this technology detect fitment problems but cannot correct them automatically.

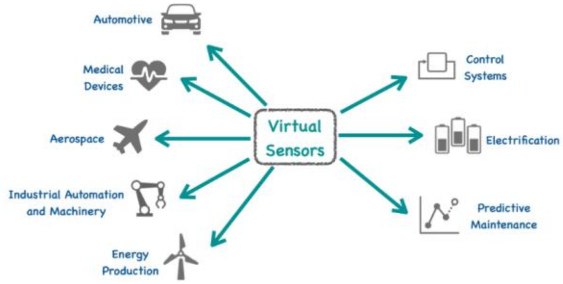

Fig 5: Virtual Sensors with AI

5.2. Data Cleaning Techniques The research articles concerning visual inspection in automotive assembly line environments have demonstrated a considerable improvement when it comes to the new recent development process. However, advancements in the field of deep-learning techniques and growth of image data from the assembly process lead to the necessity to construct new suitable development environments with respect to selecting deeper characteristics and emerging new quality-related problems, since quality issues have the nature of emergence. Utilized technical equipment has several sources creating a data-infrastructure complex without tiers or layers. This brings extra difficulties in the analysis of data and causes many data-integration problems. As a consequence of the projected future condition of the automotive assembly line, the flexible efficient development environment is presented in the form of tools, techniques, and processes. The development route has definite steps and suggests at the same time issues for further research. Quality control is one of the key activities performed by many manufacturing enterprises to ensure that manufactured products meet quality standards. With the growing production rates and technological complexity of manufactured products, the cost of on-site defects increases drastically. A defect in a manufactured product can lead to high costs for warranty coverage or dismissal of the supplier. It could also result in a substantial drop in sales and potential damage to the brand's reputation, which could take years to recover from. Therefore, an automated inspection, i.e. detecting defects before they leave the production site, is desirable. The decreased cost of sensors and connectivity has enabled an increasing digitalization of manufacturing. Digitalization can be perceived as a buzzword, but in particular, by collecting data from machines, an enormous amount of data is generated that can be analyzed in many different ways. Examples are predictive maintenance applications, organizing logistics, and taking actions on product quality. The analysis of issues concerning product quality has direct financial consequences. Data-driven approaches for statistical analysis or machine learning can be applied to aggregate data throughout several production days or weeks, and therefore trending issues and making predictions of expected defective products is possible. Thus, overall costs and time required for defect inspection can be reduced. A more typical data-driven approach for visual inspection is done at a local level. Data-driven visual inspection of manufactured products answers questions like whether a product is good or defective, and what type of defects can be found. The authors recently proposed a stepwise approach for implementing automated visual inspection based on deep learning techniques.

6. Feature Engineering for Quality Control

There are a variety of features typically employed for automated visual inspection. Initially, it is broadly categorized into global and local features. Global features describe the image in a larger context, while local descriptors characterize local patterns in objects. The features may be defined both manually and automatically. Although some handcrafted features describing textures can be widely used, they might not always be applicable to new scenarios. As the approaches become more sophisticated, the deep learning model can automatically extract discriminative features for defect detection.

Global features capture images or industry objects at a broader level. Simple pixel-wise features, such as color or intensity histograms, can provide a basic understanding of the object and are often applied to tasks like product classification. Moreover, a more complicated histogram of oriented gradient is used for general purposes commonly to obtain the shape information of 2D images. However, the performance heavily depends on the image resolution, and more importantly, they result in lower accuracy.

Local features characterize image objects through local patterns, with certain invariance properties towards geometric transformations and illumination changes. Local feature extracting might be required for several reference images, thus cannot be directly accessible for a newly arrived inspection image. Well-known local feature descriptors typically include Speeded Up Robust Features, Scale Invariant Feature Transform, and local binary patterns. These features are very successful but suffer from the expensive computational cost for real-time inspection. In recent years, several approaches based on Convolutional Neural Networks have been proposed and demonstrated the applicability of product quality assurance, tool condition monitoring, fault detection, and classification. The deep model is pre-trained for specified tasks; and some feature maps are extracted to represent the input image. Then, different models are employed, including clustering, SVM, knn, naive Bayes classifier, and others. One of the major advantages of using pre-trained deep features is avoiding the subsequent model training.

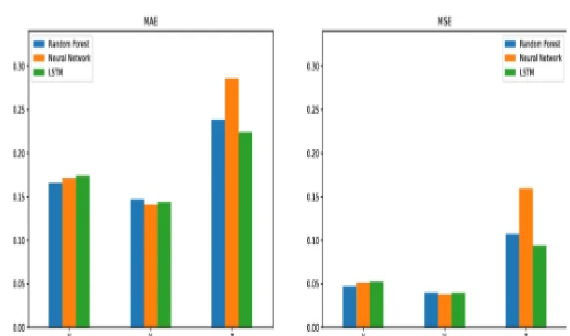

Fig : Using machine learning prediction models for quality control a case study from the automotive industry

6.1. Identifying Relevant Features Real-time detection of defects in automotive assembly lines would require evaluating two types of features: image features and time series features. 2D image features help detect component assembly defects, while time series features reflect the mechanical states of an assembly robot over time and can capture moving assembly defects. As components in an assembly line may have various geometric structures, diverse defects, and random background noise, it is often difficult to extract sufficient image features for the detection task. Pretrained CNNs are often employed to extract rich image features. In this way, the feature extraction is driven by a large amount of labeled image data, with the robustness improved by removing redundant information. Deep networks have been successfully used for machinery vision tasks for years.

Time series features can provide a generalizable way to detect moving component defects on an assembly line. Moving defects occur frequently in synchronous assembly lines, which can lead to mass rework or consumer complaints. With the popularity of data-driven methods, time series-based approaches for detecting moving defects have received increasing interest. The main difficulty is that the same component can have various possible orientations when entering the assembly station. One approach for invariant feature extraction is based on data transformation, which includes manually learned invariant transformations. Another approach is end-to-end training of a CNN on input time series signals, followed by fault classification. However, it requires a large number of labeled instances for each class, which may be costly or impossible in practice. An alternative is to train models with a few labeled data and use them to label a large amount of streaming unlabeled data, called semi-supervised learning, which has been widely studied in the computer vision field and is becoming popular in time series learning.

6.2. Dimensionality Reduction Techniques In practice, nearly all real-world data sets involve several tens or hundreds of features. These features usually contain redundant or irrelevant information for the machine learning model. Researching methods to reduce the number of features of an indicator matrix is a common approach in machine learning. provide a comprehensive overview of feature selection methods, classifying them into three categories: filter methods, wrapper methods, and embedded methods. The filter methods first evaluate feature subsets using a certain statistical measure. In the selected subset of features, the performance of the model is improved by using those features. The filter methods can scale very well. However, a good feature subset is often different for different learning models. It is hard to find a unique and most representative measure to evaluate models in terms of selection of features.

The wrapper methods select and evaluate the training set features according to the model performance. These methods are much more computationally expensive than filter methods; however, they often yield a better feature subset than filter methods, which depends on the accuracy of the performance measures. This method is sensitive to noise with learning of data. It is less general as it is tied to a specific model and the computation cost is heavy.

The embedded methods, which are inherently incorporated in the learning model, employ sparsity on the weight of the model to discard irrelevant features. They are less computationally expensive than wrapper methods . Since the performance of those features discarded is neglected, it is often difficult to make sure which discarded features behave well. Two embedded methods are selected as representatives, which are linear regression and probabilistic PCA.

Equ 3: Supervised Learning for Defect Detection (Classification)

$$P(y = 1|\mathbf{x}) = \frac{1}{1 + e^{-(\mathbf{w}^\top \mathbf{x} + b)}}$$

Where:

- $y \in \{0, 1\}$ indicates whether the part passes
- $\mathbf{w}$ and b are learned parameters

7.

Conclusion

The automotive industry is constantly changing due to new manufacturing technologies and customer demands for flexibility and more dedicated models. Assembly and production processes are being adapted to achieve target outputs using iterative simulations. New-on-the-market methods enable drastically shorter cycle-time scenarios to be investigated before deployment. Shorter assemblies require enormous parallelism and oven usage dynamics, variable temperatures, control optimizations, and ultimately new flavors of machine learning.

Conventional machine learning methods cannot be deployed on control signals. Sensor measurements are fed into convolutional networks that classify whether constraints are met. Privacy concerns regarding cloud connections require on-premise processing of large amounts of data. State-of-the-art methods process internal features of trained models and resemble dimensionality reduction techniques. They cannot be re-trained or initialized using a smaller dataset coming from a previously deployed model without exploiting carefully crafted test cases. Care must be taken regarding the invariance properties of new feature encodings.

Decisions from classical algorithms and neural models can be visualized using local explanations. These require retraining the underlying model for each deviation from nominal conditions of an episode. Only a single-case approximation of the model is provided, which must be interpreted by a domain expert for possible mislearning or drifting. Explaining anomalies results in a divide-and-conquer paradigm, requiring a new model if any change is made to the production site. On the other hand, intuition-enhanced models can explain their predictions using learned physical laws. Such models are rarely applied since most derived quantities are not affected by modeling choices. Their transparency is exploited in this regard. Some visualizations highlight defective parts by inpainting them. It is severely limited to extra models and preconfigured tolerances from assembly plant engineering documents, making it completely new to the chosen scenario.

The discussants considered all advantages and disadvantages. First attempts were made to jointly train classical and neural networks. Object detection frameworks can be adapted for such applications. Hyperparameters, the state of initial hyperparameters, and other inputs were subject to uncertainty. Further investigations are planned by exploiting graphical models. Much effort is invested in the visualization of the inner workings of the neural network and hand-coding rules for parts passing and failing processing using time-series segmentation. Regardless of the solution ultimately chosen, classical post-processing and machine learning can be integrated into an adaptable pipeline.

7.1. Future Trends The automation of condition monitoring and workpiece inspection plays an essential role in maintaining high quality and high throughput of the manufacturing process. Workpiece inspection based on machine learning (ML) is the second important step in a complete automation pipeline and it aims to detect the presence of defects on the workpiece before it leaves the machining area. The developments in ML have led to improvements in autonomous process supervision. However, one main challenge to ensure broad acceptance in industrial environments is the monitoring of live deployments of these ML systems and raising alerts when encountering events that might impact model performance. A critical aspect that affects model performance is the stability of the data distribution. Supervised classifiers are typically built under the assumption of stationarity in the underlying data distribution. However, in many real-world applications, this assumption is violated because of the occurrence of data drift. Data drift can mean gradual changes of the underlying data distribution as, for example, the emergence of new types of surface defects. Thus, it is desirable to provide real-time tracking of a classifier’s performance to inform about the onset of additional error classes for the use case of workpiece inspection and the necessity for manual intervention with respect to classifier re-training.

Today’s increased level of automation in manufacturing is accompanied by the need for a similarly increased level of automation of material quality inspection with minimal human intervention. The transition from manual to automated quality inspection is an important step toward meeting both quantity and quality goals in production without compromising one over the other. However, even after the transition to quality inspection systems that rely on ML analyses of data from sensors, it is imperative to be able to point out selection of error class and severity of error class for a detected workpiece. With today’s increased level of automation in manufacturing, manufacturers strive to achieve both quantity and quality of production without compromising one over the other. With advances in Artificial Intelligence, manufacturers have begun to employ such technologies during the production cycle to automate quality inspection and monitor machine conditions. By doing so, it is possible to optimize factory capacities.

8. References

[1] Vankayalapati, R. K. (2020). AI-Driven Decision Support Systems: The Role Of High-Speed Storage And Cloud Integration In Business Insights. Available at SSRN 5103815.

[2] Sondinti, L. R. K., & Yasmeen, Z. (2022). Analyzing Behavioral Trends in Credit Card Fraud Patterns: Leveraging Federated Learning and Privacy-Preserving Artificial Intelligence Frameworks.

[3] Kannan, S. (2022). The Role Of AI And Machine Learning In Financial Services: A Neural Networkbased Framework For Predictive Analytics And Customercentric Innovations. Migration Letters, 19(6), 985-1000.

[4] Harish Kumar Sriram. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Mathematical Statistician and Engineering Applications, 71(4), 16729–16748. Retrieved from https://philstat.org/index.php/MSEA/article/view/2966

[5] Chava, K. (2022). Redefining Pharmaceutical Distribution With AI-Infused Neural Networks: Generative AI Applications In Predictive Compliance And Operational Efficiency. Migration Letters, 19(S8), 1905-1917.

[6] Komaragiri, V. B. (2022). AI-Driven Maintenance Algorithms For Intelligent Network Systems: Leveraging Neural Networks To Predict And Optimize Performance In Dynamic Environments. Migration Letters, 19, 1949-1964.

[7] Chakilam, C. (2022). Generative AI-Driven Frameworks for Streamlining Patient Education and Treatment Logistics in Complex Healthcare Ecosystems. Kurdish Studies. Green Publication. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3719.

[8] Nuka, S. T. (2022). The Role of AI Driven Clinical Research in Medical Device Development: A Data Driven Approach to Regulatory Compliance and Quality Assurance. Global Journal of Medical Case Reports, 2(1), 1275.

[9] Burugulla, J. K. R. (2022). The Role of Cloud Computing in Revolutionizing Business Banking Services: A Case Study on American Express's Digital Financial Ecosystem. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3720.

[10] Pamisetty, A. (2022). Enhancing Cloud native Applications WITH Ai AND Ml: A Multicloud Strategy FOR Secure AND Scalable Business Operations. Migration Letters, 19(6), 1268-1284.

[11] Anil Lokesh Gadi. (2022). Transforming Automotive Sales And Marketing: The Impact Of Data Engineering And Machine Learning On Consumer Behavior. Migration Letters, 19(S8), 2009–2024. Retrieved from https://migrationletters.com/index.php/ml/article/view/11852

[12] Someshwar Mashetty. (2022). Enhancing Financial Data Security And Business Resiliency In Housing Finance: Implementing AI-Powered Data Analytics, Deep Learning, And Cloud-Based Neural Networks For Cybersecurity And Risk Management. Migration Letters, 19(6), 1302–1818. Retrieved from https://migrationletters.com/index.php/ml/article/view/11741

[13] Pandiri, L., & Chitta, S. (2022). Leveraging AI and Big Data for Real-Time Risk Profiling and Claims Processing: A Case Study on Usage-Based Auto Insurance. In Kurdish Studies. Green Publication. https://doi.org/10.53555/ks.v10i2.3760

[14] Recharla, M., & Chitta, S. (2022). Cloud-Based Data Integration and Machine Learning Applications in Biopharmaceutical Supply Chain Optimization.

[15] Nandan, B. P., & Chitta, S. (2022). Advanced Optical Proximity Correction (OPC) Techniques in Computational Lithography: Addressing the Challenges of Pattern Fidelity and Edge Placement Error. Global Journal of Medical Case Reports, 2(1), 58–75. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1292

[16] Srinivasarao Paleti. (2022). Adaptive AI In Banking Compliance: Leveraging Agentic AI For Real-Time KYC Verification, Anti-Money Laundering (AML) Detection, And Regulatory Intelligence. Migration Letters, 19(6), 1253–1267.

[17] Pallav Kumar Kaulwar. (2022). Data-Engineered Intelligence: An AI-Driven Framework for Scalable and Compliant Tax Consulting Ecosystems. Kurdish Studies, 10(2), 774–788. https://doi.org/10.53555/ks.v10i2.3796

[18] Koppolu, H. K. R. (2022). Advancing Customer Experience Personalization with AI-Driven Data Engineering: Leveraging Deep Learning for Real-Time Customer Interaction. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3736.

[19] Dodda, A. (2022). Strategic Financial Intelligence: Using Machine Learning to Inform Partnership Driven Growth in Global Payment Networks. International Journal of Scientific Research and Modern Technology, 1(12), 10–25. https://doi.org/10.38124/ijsrmt.v1i12.436

[20] Jeevani Singireddy,. (2022). Leveraging Artificial Intelligence and Machine Learning for Enhancing Automated Financial Advisory Systems: A Study on AIDriven Personalized Financial Planning and Credit Monitoring. Mathematical Statistician and Engineering Applications, 71(4), 16711–16728. Retrieved from https://philstat.org/index.php/MSEA/article/view/2964

[21] Challa, S. R. (2022). Optimizing Retirement Planning Strategies: A Comparative Analysis of Traditional, Roth, and Rollover IRAs in LongTerm Wealth Management. Universal Journal of Finance and Economics, 2(1), 1276.

[22] Lakkarasu, P., & Kalisetty, S. Hybrid Cloud and AI Integration for Scalable Data Engineering: Innovations in Enterprise AI Infrastructure

[23] Ganti, V. K. A. T., & Valiki, S. (2022). Leveraging Neural Networks for Real-Time Blood Analysis in Critical Care Units. KURDISH. Green Publication. https://doi. org/10.53555/ks. v10i2, 3642.

[24] Kothapalli Sondinti, L. R., & Syed, S. (2022). The Impact of Instant Credit Card Issuance and Personalized Financial Solutions on Enhancing Customer Experience in the Digital Banking Era. Universal Journal of Finance and Economics, 1(1), 1223. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1223

[25] Annapareddy, V. N. (2022). Innovative Aidriven Strategies For Seamless Integration Of Electric Vehicle Charging With Residential Solar Systems. Migration Letters, 19(6), 1221-1236.

[26] Sriram, H. K. (2022). AI Neural Networks In Credit Risk Assessment: Redefining Consumer Credit Monitoring And Fraud Protection Through Generative AI Techniques. Migration Letters, 19(6), 1017-1032.

[27] Komaragiri, V. B., & Edward, A. (2022). AI-Driven Vulnerability Management and Automated Threat Mitigation. International Journal of Scientific Research and Management (IJSRM), 10(10), 981-998.

[28] Chakilam, C. (2022). Integrating Generative AI Models And Machine Learning Algorithms For Optimizing Clinical Trial Matching And Accessibility In Precision Medicine. Migration Letters, 19, 1918-1933.

[29] Malempati, M. (2022). Machine Learning and Generative Neural Networks in Adaptive Risk Management: Pioneering Secure Financial Frameworks. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3718.

[30] Challa, K. (2022). Generative AI-Powered Solutions for Sustainable Financial Ecosystems: A Neural Network Approach to Driving Social and Environmental Impact. Mathematical Statistician and Engineering.

[31] Anil Lokesh Gadi. (2022). Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention. Journal of International Crisis and Risk Communication Research , 11–28. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2965

[32] Srinivasarao Paleti. (2022). Fusion Bank: Integrating AI-Driven Financial Innovations with Risk-Aware Data Engineering in Modern Banking. Mathematical Statistician and Engineering Applications, 71(4), 16785–16800.

[33] Pallav Kumar Kaulwar. (2022). Securing The Neural Ledger: Deep Learning Approaches For Fraud Detection And Data Integrity In Tax Advisory Systems. Migration Letters, 19(S8), 1987–2008. Retrieved from https://migrationletters.com/index.php/ml/article/view/11851

[34] Dodda, A., Lakkarasu, P., Singireddy, J., Challa, K., & Pamisetty, V. (2022). Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies.

[35] Operationalizing Intelligence: A Unified Approach to MLOps and Scalable AI Workflows in Hybrid Cloud Environments. (2022). International Journal of Engineering and Computer Science, 11(12), 25691-25710. https://doi.org/10.18535/ijecs.v11i12.4743

[36] Vankayalapati, R. K., & Pandugula, C. (2022). AI-Powered Self-Healing Cloud Infrastructures: A Paradigm For Autonomous Fault Recovery. Migration Letters, 19(6), 1173-1187.

[37] Kalisetty, S., Vankayalapati, R. K., Reddy, L., Sondinti, K., & Valiki, S. (2022). AI-Native Cloud Platforms: Redefining Scalability and Flexibility in Artificial Intelligence Workflows. Linguistic and Philosophical Investigations, 21(1), 1-15.

[38] Sriram, H. K. (2022). Integrating generative AI into financial reporting systems for automated insights and decision support. Universal Journal of Finance and Economics, 2(1), 115–131. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1299

[39] Malempati, M. (2022). AI Neural Network Architectures For Personalized Payment Systems: Exploring Machine Learning's Role In Real-Time Consumer Insights. Migration Letters, 19(S8), 1934-1948.

[40] Vamsee Pamisetty, Lahari Pandiri, Sneha Singireddy, Venkata Narasareddy Annapareddy, Harish Kumar Sriram. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Migration Letters, 19(S5), 1770–1784. Retrieved from https://migrationletters.com/index.php/ml/article/view/11808

[41] Kishore Challa, Jai Kiran Reddy Burugulla, Lahari Pandiri, Vamsee Pamisetty, Srinivasarao Paleti. (2022). Optimizing Digital Payment Ecosystems: Ai-Enabled Risk Management, Regulatory Compliance, And Innovation In Financial Services. Migration Letters, 19(S5), 1748–1769. Retrieved from https://migrationletters.com/index.php/ml/article/view/11807

[42] Botlagunta Preethish Nadan. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Mathematical Statistician and Engineering Applications, 71(4), 16749–16773. Retrieved from https://philstat.org/index.php/MSEA/article/view/2967

[43] Kaulwar, P. K. (2022). The Role of Digital Transformation in Financial Audit and Assurance: Leveraging AI and Blockchain for Enhanced Transparency and Accuracy. Mathematical Statistician and Engineering Applications, 71 (4), 16679–16695.

[44] Karaka, L. M. (2021). Optimising Product Enhancements Strategic Approaches to Managing Complexity. Available at SSRN 5147875.

[45] Katnapally, N., Murthy, L., & Sakuru, M. (2021). Automating Cyber Threat Response Using Agentic AI and Reinforcement Learning Techniques. J. Electrical Systems, 17(4), 138-148.

[46] Boppana, S. B., Moore, C. S., Bodepudi, V., Jha, K. M., Maka, S. R., & Sadaram, G. (2021). AI And ML Applications In Big Data Analytics: Transforming ERP Security Models For Modern Enterprises.

[47] Chinta, P. C. R., & Karaka, L. M.(2020). AGENTIC AI AND REINFORCEMENT LEARNING: TOWARDS MORE AUTONOMOUS AND ADAPTIVE AI SYSTEMS.

[48] Velaga, V. (2022). Enhancing Supply Chain Efficiency and Performance Through ERP Optimization Strategies.